

# Classification and Soil Moisture Determination of Agricultural Fields

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## 1 Introduction

During the Mac-Europe campaign of 1991 several SAR experiments were carried out in the Flevoland test area in the Netherlands. The testsite consists of a forested and a agricultural area with more than 15 different crop types. The experiments took place in June and July (mid to late growing season).

The area was monitored by the spaceborne C-band VV polarised ERS-1, the Dutch airborne PHARS with similar frequency and polarisation and the three-frequency (P-, L- and C-band) polarimetric AIR-SAR system of NASA/JPL. The last system passed over on June 15, July 3, 12 and 28. The last two dates coincided with the overpasses of the PHARS and the ERS-1. Comparison of the results showed that backscattering coefficients from the three systems agree quite well (van den Broek and Groot, 1993).

In this paper we present the results of a study of crop type classification (section 2) and soil moisture determination in the agricultural area (section 3). For these studies we used field averaged Stokes matrices extracted from the AIRSAR data (processor version 3.55 or 3.56).

## 2 Classification of agricultural fields

Field averaged Stokes matrices contain five non-zero cross products ( $\sigma_{hh} = \langle S_{hh} S_{hh}^* \rangle$ ,  $\sigma_{vv} = \langle S_{vv} S_{vv}^* \rangle$ ,  $\sigma_{hv} = \langle S_{hv} S_{hv}^* \rangle$ ,  $\rho = \langle S_{hh} S_{vv}^* \rangle$ ), where the last cross product is complex. The  $\langle S_{co} S_{cross}^* \rangle$  products are zero due to azimuthal symmetry. We use here two classification methods: a Gaussian maximum likelihood (GML) method which uses the polarimetric information directly and the so-called polarimetric contrast classification (PCC) method which uses this information more indirectly. For the study of crop type classification we have selected 330 agricultural fields with 8 crop-type classes (see Table)

crop type	#fields	crop type	#fields
rapeseed	13	sugar beet	63
grass	41	corn	15
potato	86	barley	19
wheat	84	beans	9

### 2.1 Gaussian maximum likelihood classification

This method deals with feature vectors of arbitrary dimensionality. We can use single features as C-band  $\sigma_{vv}^0$  (ERS-1), full polarimetric vectors as  $X = (\sigma_{hh}^0, \sigma_{vv}^0, \sigma_{hv}^0, \rho)$  or multi-temporal vectors as  $X = (\sigma_{15/6}^0, \sigma_{3/7}^0, \sigma_{12/7}^0, \sigma_{28/7}^0)$  for one particular polarisation combination. We obtain ensemble statistics for every crop-type class by calculating the mean vector  $\mu_i = E[X_i]$  and the covariance matrix  $C_{ij} = E[(x_i - \mu_i)(x_j - \mu_j)^\dagger]$  with  $E$  the expectation value. Next we calculate for every field the distance function  $D$  defined by

$$D = -\frac{1}{2} \log |C| - \frac{1}{2} (X_i - \mu_i) C_{ij}^{-1} (X_j - \mu_j) \quad (1)$$

to all crop-type classes. The field is assigned to that crop-type class for which this distance is a minimum.

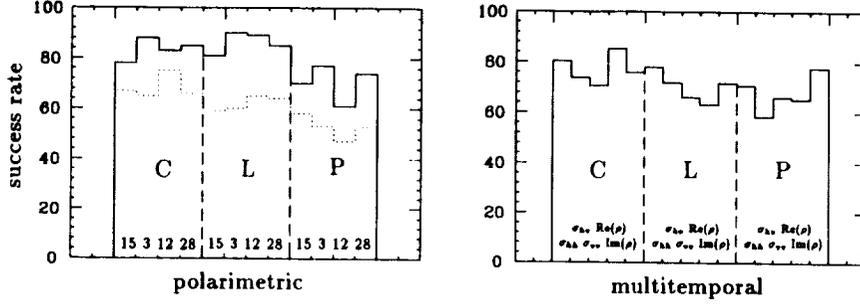


Figure 1: Classification results with the GML (full line) and PCC (dotted line) method using polarimetric (Fig. 1a, left) and multitemporal features (Fig. 1b, right).

## 2.2 Polarimetric contrast classification

This method was originally introduced by Kong (1990). It uses the so-called optimum contrast  $\lambda$  between two Stokes matrices  $M_a$  and  $M_b$ , which is defined by

$$\lambda = \frac{s^T M_a s}{s^T M_b s} \quad (2)$$

where the polarisation state of Stokes vector  $s$  is chosen such that  $\lambda$  is an extremum. In this method first the ensemble averages of the Stokes matrices for all crop-type classes are calculated. Then for each field we calculate the optimum contrast with all crop-type classes and the field is assigned to that class for which the optimum contrast is a minimum.

## 2.3 Results

Single feature classification success percentages are between 30 and 50%. Generally the  $\sigma_{hh}^0$  results are better than the  $\sigma_{vv}^0$  results. The best results are obtained for the C- and L-band  $\sigma_{hh}^0$  on July 3.

The C- and L-band polarimetric success percentages are on average 60% for the PCC method and 80% for the GML method (see Fig. 1a). The P-band results are significantly lower for both methods, since the backscatter of the soil dominates that of the vegetation here.

When single features of the 4 dates are combined into multi-temporal feature vectors success percentages of 70 to 80% are found (see Fig. 1b), so that it can be concluded that single day polarimetric classification is more powerful than 4 day multitemporal classification in the mid to late growing season. This situation may change when also data obtained in the beginning of the growing season is used.

## 3 Soil moisture determination of vegetated soil

For bare soil it is in principle possible using radar to measure the top-layer soil moisture content if the soil roughness is known, since the radar backscatter from soil primarily depends on the soil moisture content and soil roughness. However, when the soil is vegetated we have to know the transmissivity of the vegetation layer and also the relative contributions in the backscatter of the vegetation and of the soil. This information cannot be obtained from single frequency and single polarisation systems (e.g. the ERS-1), but maybe obtained from the three-frequency polarimetric AIRSAR system. Every measurement with this system delivers 15 features (5 features for each frequency band, see Sect. 2), which are certainly not all independent, so that the dimensionality of the data-set is less than 15. If the dimensionality of the data-set remains high enough, however, the information can possibly be used to solve for the different contributions in the backscatter of vegetated soil.

### 3.1 Description of the method

In order to extract the different contributions in the backscatter from vegetated soil we adopt the simple model of Freeman and Durden (1992, hereafter the FD model). This model transforms the polarimetric information  $(\sigma_{hh}^0, \sigma_{vv}^0, \sigma_{hv}^0, \rho)$  into backscattering coefficients for diffuse, odd- and even-bounce scattering, which are related to the interaction of the microwave radiation with the vegetation, with the ground and with both the vegetation and the ground, respectively. Here we assume this is true for at least the C- and L-band. For the P-band the diffuse scattering is certainly also affected by the soil. The diffuse scattering in the model is estimated by assuming that the scatterers in the vegetation medium can be represented by uniformly oriented and distributed small dipoles (needles). The ratio of the cross- and co-polarised backscattering coefficient, which we call here the vegetation structure parameter  $\tau$ , is in this case 1/3. The derived backscattering coefficient for the vegetation is directly related to this parameter.

The derived backscattering coefficient for the soil is related to the true backscattering coefficient by

$$\sigma_{true}^0 = \Upsilon_f \sigma_{soil}^0(m_v, \sigma', f, \theta) = e^{-\alpha f} \sigma_{soil}^0(m_v, \sigma', f, \theta) \quad (3)$$

where  $\Upsilon_f$  is the two-way transmissivity of the vegetation layer depending on the frequency  $f$ ,  $\sigma'$  the soil roughness,  $\theta$  the incidence angle and  $m_v$  the volumetric soil moisture content. If we assume similarly as in the FD model that the vegetation backscattering is due to uniformly oriented small needles the transmissivity is described by  $\Upsilon_f = e^{-\alpha f}$ . If we have in addition an accurate model describing the backscattering coefficients of the soil as a function of the depending parameters, and if the soil roughness  $\sigma'$  is known Eq. (3) contains only two unknowns  $\alpha$  and  $m_v$ . In that case we can solve for  $\alpha$  and  $m_v$ , once the C- and L-band contributions of the soil are known from the FD model<sup>1</sup>. As soil model we use the empirical model of Oh et al. (1992) which is valid for incidence angles  $> 20^\circ$  and frequencies  $> 1$  GHz.

During the campaign soil roughness measurements were performed for some agricultural fields with different crop types in Flevoland which are however generally valid since the soil composition and cultivation are quite homogeneous in Flevoland. We also obtained soil moisture measurements of a small number of fields for the principal crop types (potatoes, wheat, sugar beet and maize) in a part of the observed agricultural area. Since the soil for potatoes is cultivated in furrows and ridges, which is not described by the model of Oh et al. and the scattering by wheat and maize is often dominated by even bounce scattering (especially in the L-band), we choose to use sugar beet in this study. We found 22 sugar beet fields in the selected area, which were vegetated during the three July overpasses.

### 3.2 Results

The soil roughness  $\sigma'$  is estimated to be 1.2 cm. (Vissers and van der Sanden, 1993). Unfortunately, the uncertainty is rather large. Using this value for  $\sigma'$  we solved for  $m_v$  and  $\alpha$  requiring that the residue is less than 0.1 dB in both the C- and L-band. In this way we obtained solutions for 7, 8 and 18 fields for July 3, 12 and 28, respectively. In Fig. 2a we show histograms of  $m_v$ ,  $\Upsilon_C$  and  $\Upsilon_L$  for July 28. The average soil moisture content is  $0.5 \text{ g cm}^{-3}$  and the average transmissivity is 0.45 and 0.80 in the C- and L-band, respectively.

The measured soil moisture content in three sugar beet fields is about 0.25 (Vissers and van der Sanden, 1993) so that the derived value is too high, although values derived from radar measurement may be somewhat higher due to the big water-rich roots of the sugar beet plant. Also the value for the transmissivity in the C-band is rather high, since Bouman (1991) found that the vegetation layer of sugar beet in the C-band is probably opaque, so that values less than 0.3 are expected for  $\Upsilon_C$ .

It appears that the solutions are rather sensitive to the value of the soil roughness parameter  $\sigma'$  and to the vegetation structure parameter  $\tau$ . If we estimate this value from measurements in the C-band,

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<sup>1</sup>A problem may be that the penetration depth is wavelength dependent ( $\sim \lambda/3$ ), so that different frequencies probe different soil moisture contents. We assume here that these differences are small in this context.

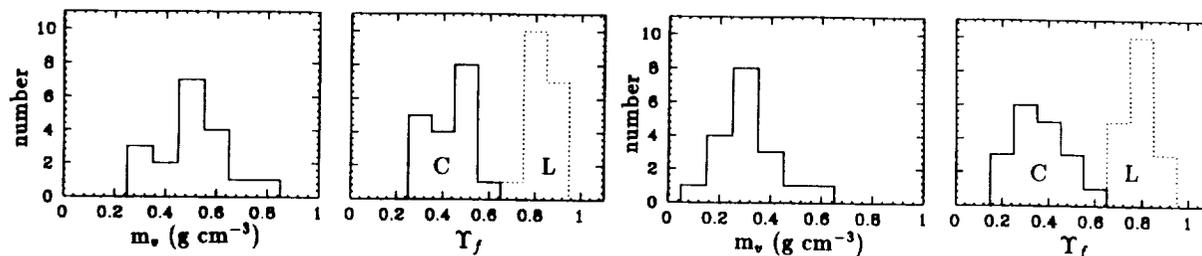


Figure 2: Histograms of  $m_v$ ,  $\Upsilon_C$  and  $\Upsilon_L$  (July 28), for  $\sigma'=1.2$  cm,  $\tau = 1/3$  (Fig. 2a, left) and  $\sigma'=1.5$  cm,  $\tau = 1/4$  (Fig 2b, right).

assuming that the contribution of the vegetation dominates that of the soil (Bouman, 1991) we find values of 0.2 - 0.3 for  $\tau$ , which is smaller than the value of 1/3 in the FD model. Clearly the structure of the sugar beet vegetation is also of importance and cannot simply be represented by small needle scatterers. If we now change the values for the vegetation structure parameter  $\tau$  to 1/4 and the soil roughness  $\sigma'$  to 1.5 cm we obtain reasonable results for July 28 (see Fig. 2b).

For July 3 and 12 no solutions were obtained in most cases, since on average the C-band soil contribution in the FD model is enhanced compared to the L-band soil contribution. This situation can be explained when the vegetation structure parameter is lower for the C-band than for the L-band, which would imply that in the period between July 12 and 28 a change in the structure parameters has occurred. Indeed, measurements with the ERS-1 in 1992 show a drop in backscattering for sugar beets during this period, which is probably related to a change in the vegetation structure (Rijckenberg, private communication).

We conclude therefore that there is an additional free parameter in the FD model, which depends on the vegetation structure and probably also on the frequency. Vegetation models like MIMICS (Ulaby et al., 1990) may help to determine this parameter. Furthermore we need to know the soil roughness quite accurately in order to apply this method successfully.

## 4 References

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